

An analysis of the short-term cloud feedback using MODIS data

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1 An analysis of the short-term cloud feedback using MODIS data

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Abstract

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The cloud feedback in response to short-term climate variations is estimated from cloud measurements combined with off-line radiative transfer calculations. The cloud measurements are made by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra satellite and cover the period 2000-2010. Low clouds provide a strong negative cloud feedback, mainly due to their impact in the shortwave (SW) portion of the spectrum. Midlevel clouds provide a positive net cloud feedback that is a combination of a positive SW feedback partially canceled by a negative feedback in the longwave (LW). High clouds have only a small impact on the net cloud feedback due to a close cancellation between large LW and SW cloud feedbacks. Segregating the clouds by optical depth, we find that the net cloud feedback is set by a positive cloud feedback due to reductions in the thickest clouds (mainly in the SW) and a cancelling negative feedback from increases in clouds with moderate optical depths (also mainly in the SW). The global average SW, LW, and net cloud feedbacks are $+0.30\pm1.10$, -0.46 ± 0.74 , and -0.16 ± 0.83 W/m²/K, respectively. The SW feedback is consistent with previous work; the MODIS LW feedback is lower than previous calculations and there are reasons to suspect it may be biased low. Finally, it is shown that the apparently small control that global mean surface temperature exerts on clouds, which leads to the large uncertainty in the short-term cloud feedback, arises from statistically significant but offsetting relationships between individual cloud types and global mean surface temperature.

1. Introduction

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Clouds cover about two thirds of the Earth's surface and substantially regulate the Earth's radiation budget. They cool the planet by reflecting shortwave (SW, 0.2-4 µm) radiation back to space, and warm it by reducing outgoing longwave (LW, > 4.54 µm) radiation. In our present climate, the SW effect dominates, so the net effect of clouds is to cool the planet (e.g., Allan, 2011). As the climate warms, however, the effect of clouds on the planet's radiation balance may also change, resulting in a feedback to the global climate system. Uncertainty in the magnitude of this cloud feedback is one of the primary contributors to the large spread of climate sensitivity estimated by general circulation models (GCMs) (e.g., Dufresne and Bony, 2008). Therefore, improving our understanding of the cloud feedback is an important step for improving our confidence in predictions of future climate change. Many previous studies have examined the cloud feedback in GCMs in response to longterm global warming (Colman, 2003; Soden and Held, 2006; Dessler, 2012), finding a cloudfeedback magnitude ranging from near zero to > 1 W/m²/K. There are, however, few estimates from observations, mainly owing to the dearth of data of appropriate length and quality. Dessler (2010; 2012) used measurements of top-of-atmosphere (TOA) flux from the Clouds and the Earth's Radiant Energy System (CERES) and estimated that the cloud feedback in response to short-term climate variations is positive and has a magnitude of $\sim +0.5\pm0.8 \text{ W/m}^2/\text{K}$. Other studies have investigated regional cloud feedbacks in observations. Clement et al. (2009) used a cloud dataset from the Northeast Pacific to show that low clouds in that region acted as a positive feedback to multi-decadal regional surface temperature changes. The GCMs that best reproduced the cloud behavior in that region and on that timescale had

average or stronger positive global cloud feedbacks in response to long-term global warming (see also Broccoli and Klein, 2010). Zelinka and Hartmann (2011) showed that high tropical clouds rose and contracted in area in response to interannual warming, leading to a net positive short-term cloud feedback from these types of clouds, although the cloud anomalies differed in subtle ways from those occurring under long-term warming (Zelinka and Hartmann 2010).

In this study, direct satellite observations of cloud properties are used to further investigate the details of the short-term cloud feedback, including comparisons to the cloud feedback calculations of Dessler (2010; 2012). In addition to providing an independent estimate of the short-term cloud feedback, this study is novel in that we will partition the cloud feedback by cloud type. This allows us to clearly identify the role of robust but opposing cloud changes in producing the net global cloud feedback. While it is unclear what the short-term cloud feedback tells us about the cloud feedback in response to long-term global warming (Dessler, 2010; 2012), the short-term cloud feedback nevertheless provides a useful testbed for our theories of the cloud feedback and as a test of climate models.

2. Data and methodology

Our cloud feedback calculations use cloud observations made by the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's Terra satellite (Platnick *et al.*, 2003). We analyze here monthly joint histograms of cloud-top pressure (P_{top}) and cloud optical depth (τ) from the MOD08 product (Hubanks *et al.*, 2008) and covering the period March 2000 to February 2010. Figure 1a plots the average cloud fraction over this period in each P_{top} - τ bin. Integration over all bins yields a total cloud fraction of 48%.

To calculate the cloud feedback, we first calculate $\Delta R_{cloud}(lon, lat, P_{top}, \tau)$, which is the contribution to the TOA flux anomaly from the cloud fraction anomaly at a particular latitude and longitude for clouds with a particular P_{top} and τ :

$$\Delta R_{cloud}(lon, lat, P_{top}, \tau) = \frac{\partial R}{\partial C(P_{top}, \tau)} \times \Delta C(lon, lat, P_{top}, \tau),$$
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where R is the TOA radiation flux and $\Delta C(\text{lon,lat,P}_{\text{top}},\tau)$ is the cloud fraction anomaly. The MODIS data provide ΔC for every month, so using Eq. (1) we can produce a monthly time series of ΔR_{cloud} . All anomalies in this paper are calculated as the departure from the mean annual cycle computed over the entire time series.

The term $\partial R/\partial C(P_{top},\tau)$ is the change in TOA flux per unit change in the fraction of clouds with a specified P_{top} and τ . These so-called cloud radiative kernels have been calculated using a radiative transfer model by Zelinka *et al.* (2012a) and are updated for this study by replacing the GCM-mean temperature, water vapor, and ozone fields used as input to the radiation code with monthly-mean fields from the ERA-Interim Reanalysis over the Terra MODIS period (Dee *et al.*, 2011). The kernels are calculated separately for SW and LW fluxes, allowing us to additionally separate the cloud feedback into SW and LW components. The kernels are functions of P_{top} , τ , latitude, month; the SW kernels are also functions of clear-sky surface albedo. Before computing ΔR_{cloud} , at each latitude we map the SW kernels from surface-albedo space to longitude using monthly climatological surface albedo from the ERA-Interim Reanalysis.

To calculate the cloud feedback for these clouds, we regress the time series of $\Delta R_{cloud}(\textit{lon,lat},P_{top},\tau) \text{ against the monthly global average surface temperature anomaly } \Delta T_s$

using an ordinary least-squares fit. The stated uncertainties in this paper are the 95% confidence interval, calculated as twice the standard error of the slope of the fit.

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3. The short-term cloud feedback from MODIS data

Figure 1b shows the slope of the linear regression of global average $\Delta C(P_{top}, \tau)$ vs. ΔT_s in each P_{top} - τ bin — this is the change in cloud fraction per degree increase in ΔT_s . The largest positive changes (i.e., ΔC increasing with increasing ΔT_s) are found in the lowest height bin (pressures > 800 hPa), with large negative changes in the bins above (800-680 hPa). Figure 2 shows the spatial distribution of the response in the 800-1000 and 680-800 hPa layers. The dominant response of clouds in both layers to changes in ΔT_s occurs over the oceans. In the 800-1000 hPa layer, positive responses occur over wide areas of the oceanic subtropics and mid-latitudes. In the 680-800 hPa layer, the dominant responses are more localized and negative, and primarily located over the ocean to the west of N. and S. America and Australia. Figures 1c, 1d, and 1e show the global average net, SW, and LW cloud feedbacks, respectively, in each cloud-top pressure/optical depth bin. To obtain these values, $\Delta R_{\text{cloud}}(lon, lat, P_{\text{top}}, \tau)$ is first averaged over all latitudes and longitudes, and then the global average $\Delta R_{cloud}(P_{top}, \tau)$ is regressed against ΔT_s to obtain the cloud feedback in each P_{top} , τ bin. All other average cloud feedbacks are calculated similarly, by first averaging ΔR_{cloud} and then regressing that average against ΔT_s . The global average cloud feedbacks are summarized in Table 1. As pointed out by Dessler and Loeb (2012) and confirmed here, the choice of ΔT_s data set can have a significant impact on the calculated cloud feedback. Aside from the MERRA, all of the calculations produce slightly negative net feedbacks (although statistically indistinguishable from zero),

which arise from a combination of a positive SW feedback and a larger negative LW feedback. The MERRA seems to be an outlier in this regard — it predicts both a negative SW and LW feedback. It is unclear why the MERRA result stands out, although given the uncertainty in the fits, it could just be a statistical fluctuation. Averaging all of the calculations together and combining the uncertainties in quadrature, the SW, LW, and net cloud feedbacks are $\pm 0.30\pm 1.10$, $\pm 0.46\pm 0.74$, and $\pm 0.16\pm 0.83$ W/m²/K (excluding the MERRA results yields values of $+0.42\pm1.13$, -0.51 ± 0.75 , -0.10 ± 0.84 W/m²/K). All subsequent calculations in the paper, including all of the figures, use the GISTEMP ΔT_s data set (Hansen et al., 2010). Also listed in Table 1 are cloud feedback values calculated using CERES measurements (Dessler, 2012; Dessler and Loeb, 2012; Dessler, 2010). CERES measures the TOA net flux; ΔR_{cloud} is calculated from those measurements by subtracting off the effects of changing water vapor, surface and atmospheric temperature, surface albedo, and radiative forcing (Soden et al., 2008; Shell et al., 2008). Thus, the CERES cloud feedback is derived not just from different data, but from an entirely different method, so the comparison provides an important test of the MODIS results. The MODIS SW cloud feedback is 0.16-0.28 W/m²/K larger than the CERES SW cloud feedbacks, which is a relatively small difference considering the uncertainty. We therefore consider these quantities to be in good agreement. The MODIS LW cloud feedback is ~ 0.9 W/m²/K less than the CERES estimates, a much larger difference than for the SW feedback estimates. Combining SW and LW feedbacks leads to the net cloud feedback from MODIS observations $\sim 0.7 \text{ W/m}^2/\text{K}$ lower than that from the CERES observations — a big enough difference that the net feedback in the MODIS and CERES calculations have different signs.

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To explore these differences in more detail, Figure 3 compares the SW, LW, and net cloud feedback derived from MODIS and CERES as a function of latitude. The SW feedback comparison reveals excellent agreement between the two data sets. In the LW, the cloud feedback derived from CERES is more positive than the MODIS feedback at most latitudes. Integrating over the globe, this small difference at each latitude sums to produce the large underestimate of the global LW cloud feedback by MODIS discussed previously. In the net, there is generally good agreement between the MODIS and CERES estimates. The largest differences occur between 20°N and 60°N, where the CERES net cloud feedback is higher than that from MODIS. Thus, the main difference between these data sets is the lower LW cloud feedback from MODIS. Some of the difference can be explained by the method: Zelinka et al. (2012a) found that, in an analysis of GCMs, the cloud-kernel-derived LW cloud feedbacks were on average $0.15~\text{W/m}^2/\text{K}$ lower than those computed using the method used to analyze the CERES data. Limitations in the MODIS data may also contribute to the discrepancy. First, the optical depths of thinner clouds ($\tau < 2$) are frequently not retrieved by MODIS (e.g., Marchand et al., 2010). This includes about ~20% of the pixels identified as cloudy by the MODIS cloud mask but for which the optical depth retrieval fails as well as clouds too thin to be flagged by the cloud mask ($\tau \approx 0.3$). This is reflected in Fig. 1a, which shows few clouds in the two lowest τ bins (although other data show that clouds are indeed there (e.g., Dessler and Yang, 2003)). Second, MODIS optical depth is retrieved using a bispectral method involving both visible and near-infrared bands (King et al., 1992), so the MODIS data exclude nighttime observations, including the wintertime high latitudes. Both of these issues will affect MODIS's LW cloud feedback more than its SW feedback.

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Another potential problem is an inconsistency between the MODIS retrieved cloud-top and the kernel. The kernel assumes the cloud top height is the height of the emitting level of the cloud (i.e., one optical depth into the cloud). However, the MODIS cloud-top is retrieved by a CO₂-slicing technique that retrieves a more accurate "edge" of the cloud, which tends to be higher than the emitting level of the cloud. This will also primarily affect the MODIS LW cloud feedback. Yet another potential problem is a mismatch in the MODIS retrieval between cloud-top pressure and optical depth. For example, MODIS can correctly identify the cloud-top pressure of an optically thin high cloud over a thick lower cloud, but the retrieved optical thickness is for the whole column. This would produce the wrong LW ΔR_{cloud} when the retrieved properties of this cloud are multiplied by the LW cloud kernel (R. Pincus, personal communication, 2012), but would have much less of an effect on the SW ΔR_{cloud} . The CERES-derived global average cloud feedbacks also have uncertainties. In addition to the uncertainty in the CERES measurements, the radiative kernels used to convert the CERES measurements to ΔR_{cloud} are derived from GCMs (Soden et al., 2008; Shell et al., 2008), so may not completely represent reality. Dessler and Loeb (2012) discuss the impact of different data sets on the CERES calculation. Putting everything together, it is our judgment that the global-average cloud feedback from CERES is likely to be more reliable than the values obtained from the MODIS measurements. But even with potential global-average biases, the MODIS calculation is useful because it allows us to break the cloud feedback down by cloud type, something that

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cannot be done with the CERES data.

To further compare the MODIS and CERES cloud feedback calculations, Figure 4a and 4b show the spatial distribution of SW cloud feedback calculated from MODIS and CERES observations. Regions that contribute positively (negatively) to the cloud feedback are colored red (blue). The El Nino/La Nina Southern Oscillation (ENSO) is the dominant factor for the interannual climate variations over the period analyzed, and therefore the regional distribution of cloud feedback reflects a characteristic dipole pattern in the tropical Pacific. The difference between the MODIS and CERES cloud feedback estimates are in Fig. 4c. Clearly, the MODIS results agree well with those of CERES, capturing both the broad features and the detailed spatial structures of the cloud-induced TOA flux anomalies. Figures 4d, 4e, and 4f show the same plots for the LW. The LW feedback is essentially a mirror image of the SW feedback, a consequence of the prominent role of high cloud anomalies in causing the radiative anomalies and their opposing SW and LW effects on climate. As with the SW, the difference between CERES and MODIS estimates is small. Figures 4g, 4h, and 4i show the same plots for the net cloud feedback. This agreement in the net feedbacks is particularly notable since the net feedback is a small residual of two large but oppositely signed terms. Small errors in either the LW or SW term would lead to large errors in the net feedback — the lack of large errors increases our confidence in the cloud feedback calculations. The point-by-point agreement also means that the differences in the global average feedbacks arise from small but widely distributed biases between the two calculations.

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To investigate the breakdown of the cloud feedback by cloud property, Figure 5 shows the cloud response and cloud feedback as a function of cloud-top pressure. Fig. 5a shows the

biggest cloud changes occur for P_{top} above (altitudes below) 800 hPa. This layer by itself drives a net global cloud feedback of -1.08 \pm 0.58 W/m²/K (Fig. 5b).

At pressures below (altitudes above) 800 hPa, changes in clouds produce a weakly negative LW cloud feedback (Fig. 5d) and a strongly positive SW cloud feedback (Fig. 5c), leading to a net positive feedback of +1.06±0.69 W/m²/K (Fig. 5b). Thus, the net global cloud feedback is set by a negative feedback due to clouds near the surface and a slightly smaller positive feedback due to clouds in the rest of the troposphere. Individually, both feedbacks are statistically significant, but the sum over the whole troposphere is not. We will discuss this last point in more detail in Section 4.

The largest LW cloud feedbacks are found in the uppermost bin, covering cloud-top pressures of 180-50 hPa. The LW feedback there is negative and it plays a dominant role in producing the overall negative global LW cloud feedback. These same cloud changes generate an almost equivalent but oppositely signed SW cloud feedback (Figs. 5c). The net cloud feedback at these altitudes is therefore close to zero (Fig. 5b). Figure 10 and Table 1 of Zelinka and Hartmann (2011) show a similar amount of cancellation between LW and SW fluxes in the upper troposphere, although that study focused on the tropics. Loeb *et al.* (2012) also found a negative LW and positive SW tropical cloud feedback response to ENSO.

Figure 6 shows the distribution of the cloud changes and the associated feedbacks in the uppermost layer, and the response of these clouds is quite different from the response of low-level clouds in Fig. 2. Upper-level clouds show a classic ENSO dipole response of cloud fraction changes in the tropical Pacific, and the pattern corresponds closely to the water vapor feedback (Fig. 2 of Dessler, 2012). It is also clear that the resulting LW and SW feedbacks

substantially cancel each other — not just in the global average, but also at individual grid points.

Figure 5 also breaks down the cloud feedback at each altitude into contributions from changing cloud fraction and optical depth (in each case holding the other property fixed), calculated using methodology derived from Zelinka *et al.* (2012b). The plot shows that, at most altitudes, the cloud feedback is primarily due to changes in cloud fraction; changes in optical depth make a smaller, positive contribution, mainly in the SW.

Figure 7 shows the feedback as a function of cloud optical depth. The fraction of clouds with τ > 23 decreases with increasing ΔT_s , while the fraction of clouds with τ < 23 increases (Fig. 7a). The increase in thin clouds at the expense of thick clouds leads to offsetting SW cloud feedbacks for these two groups — summing them produces a the net positive SW cloud feedback. Figure 7 also breaks down the cloud feedback at each optical depth into contributions from changing cloud fraction and cloud top height. Changes in cloud height have little impact in the SW, so the SW cloud feedback is mainly from changing cloud fraction.

In the LW (Fig. 7d), the feedback is negative for all optical depth bins. The figure shows that this overall negative feedback arises from a general competition between changing cloud fraction and cloud top height. For the thickest clouds, the reduction in cloud fraction dominates over the increase in cloud top height, leading to a negative LW feedback. For thinner clouds, a reduction in cloud top height dominates the increase in cloud fraction, which also leads to a negative LW feedback.

The net cloud feedback comes from a positive cloud feedback from thick cloud changes and a slightly bigger negative feedback from changes in thinner clouds (Fig. 7b). Changes in

the thinnest clouds contribute little to the net feedback, although, as mentioned previously, this might be a consequence of MODIS's inability to retrieve cloud properties for these thin clouds. Indeed, tropical mean LW cloud feedbacks computed in the same manner as in this study but using ISCCP (which retrieves significantly more thin clouds than MODIS (Marchand et al., 2010)) are consistently less negative than those computed using MODIS, despite the SW cloud feedbacks being the same (Zelinka and Hartmann, 2011). Figure 8 shows the latitudinal distribution of the cloud feedback broken down into high $(P_{top} \le 440 \text{ hPa})$, mid-level $(440 \le P_{top} \le 680 \text{ hPa})$ and low $(P_{top} \ge 680 \text{ hPa})$ clouds. At most latitudes, the biggest component of the LW or SW cloud feedback is from high clouds. The LW and SW feedbacks of high clouds nearly cancel, however. This leads to a substantially smaller net high-cloud feedback that is comparable at most latitudes to the net feedback from mid-level and low clouds. The latitudinal pattern of the high cloud feedbacks primarily reflects the equatorward shift of the subtropical jets during the (warmer) El Nino phase of ENSO (e.g., Trenberth and Hurrell, 1994). This moves cloudy regions onto the Equator and the clear subtropics towards the equator — and results in the hemispherically symmetric pattern in the Tropics evident in Fig. 8a. Table 1 lists the global average cloud feedbacks broken down by altitude. Because the changes in high clouds are primarily driven by rearrangements in the atmospheric circulation, a large positive cloud feedback at one latitude will tend to be cancelled in the global average by a large negative cloud feedback at another latitude. The global average high-cloud feedbacks are therefore a small residual of these large and offsetting feedbacks from different

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latitudes.

For lower clouds, the SW cloud feedback dominates and it is what mainly determines the net cloud feedback. For mid-level clouds, the net feedback is positive at most latitudes, leading to a positive global average. While the SW and net mid-level cloud feedback is smaller at most latitudes than the low- or high-cloud counterparts, it is also rarely negative. It therefore ends up being the largest positive contributor to the global mean feedback — and is the only component that is distinguishable from zero. For low clouds, averaging over the globe produces a strong negative SW and net cloud feedback.

Overall, the global SW cloud feedback is set by a positive feedback from mid-level and high clouds, which is reduced by about 50% by a negative feedback from low clouds. The global LW feedback is negative at all altitudes, with the greatest contribution coming from high clouds. The net cloud feedback is set by a negative feedback from low clouds that is almost entirely cancelled by positive cloud feedbacks from mid-level and high clouds.

Table 1 also lists a breakdown by optical depth. Viewed this way, the positive SW cloud feedback is set by a positive feedback from thick clouds that is partially cancelled by a negative feedback from mid-thickness and thin clouds. The negative LW cloud feedback is set primarily by thick clouds, with a smaller contribution from mid-thickness clouds. The net feedback is set by a positive feedback from thick clouds that is nearly cancelled by a negative feedback from mid-thickness and thin clouds.

4. Why is the cloud feedback so uncertain?

Dessler (2010; 2012) presented scatterplots of ΔR_{cloud} , the cloud-induced TOA flux anomaly, against ΔT_s , the global average surface temperature anomaly. The MODIS ΔR_{cloud} vs. GISTEMP ΔT_s plot is shown in Fig. 9a (slope = -0.02±0.76 W/m²/K). The correlation

between these variables is poor and the scatter in the data results in a highly uncertain cloud feedback. One might conclude from this that clouds are only weakly impacted by ΔT_s variations.

Analysis of the MODIS data helps us refine our understanding of this issue. Figure 9b shows a scatterplot of ΔR_{cloud} vs. ΔT_s for the lowest layer (1000-800 hPa) (slope = -1.08±0.58 W/m²/K) and Fig. 9c shows the same thing for the rest of the troposphere (800-50 hPa) (slope = +1.06±0.69 W/m²/K). Both relations are statistically significant (although there is still considerable scatter), so one can conclude that clouds in these layers are indeed related to ΔT_s . The relationships have opposite signs, however, so when one considers the entire troposphere (Fig. 9a), they cancel and no clear relation exists.

This can also be seen in Fig. 1b-1e, in which P_{top} - τ bins that show statistically significant correlations with ΔT_s (at the 2σ level) are marked with a cross. About 40-50% of the bins show statistically significant relations (more than the 5% that would be expected due to chance), confirming in more detail the results in Fig. 9.

This reflects a general truth about these data: the global average cloud feedback is a small residual of the sum of larger and often statistically significant quantities that oppose each other horizontally, vertically, in optical depth space, and spectrally (LW vs. SW). Thus, it is not correct to conclude, on the basis of a plot like Fig. 9a, that ΔT_s has little influence on clouds. Rather, individual cloud populations may indeed be controlled by ΔT_s , but cancellations in the global average calculations obscure the relationships.

Much of this cancellation may be due to the fact that most of the climate variation we are using to extract the cloud feedback comes from ENSO, which is a large-scale rearrangement of the atmospheric circulation. This rearrangement leads to large but compensating changes

in clouds, and therefore to the cancellation identified above. GCM simulations of long-term global warming show a more uniform response, with both the LW and SW feedback being positive at most latitudes (e.g., Dessler, 2012, Fig. 6; Zelinka *et al.*, 2012a, Fig. 6).

5. Discussion and Conclusions

In this study, MODIS observations of clouds are used to estimate the cloud feedback in response to short-term climate variations. The global average net cloud feedback estimated from MODIS is slightly negative — it arises by the near-balance between a negative LW cloud feedback and a positive SW cloud feedback (Table 1).

These results have been compared to independent estimates of the cloud feedback derived from CERES TOA flux observations (Dessler, 2010; 2012). In the SW, the calculations show good agreement and both predict a positive SW cloud feedback. In the LW, however, there are significant differences: the MODIS LW feedback is negative, while that from CERES is positive. Considering all potential sources of error, we judged that the more reliable global average cloud feedback values are the ones obtained from the CERES data.

In response to short-term climate variations, the MODIS data show a strong increase in low clouds (cloud-top pressures above (altitudes below) 800 hPa) as the climate warms (Fig. 5a), primarily occurring over oceans in the subtropics and midlatitudes (Fig. 2a). These cloud changes produce a strong negative cloud feedback, almost entirely from increased SW reflection. A concomitant decrease in clouds between 800 and 500 hPa yields a nearly offsetting positive feedback, also predominantly in the SW (Fig. 5). Changes in high clouds have significant SW and LW cloud feedbacks that nearly cancel, leading to little contribution

to the global net cloud feedback (Figs. 5b and 6). Thus, the majority of the net cloud feedback comes from the lower troposphere.

Analyzing the cloud feedback as a function of optical depth (Fig. 7), the data show a general decrease of τ as ΔT_s increases. The general thinning of clouds produces a positive cloud feedback in the SW and a negative feedback in the LW.

Our results show that high clouds dominate the LW and SW cloud feedbacks at most latitudes (Fig. 8). There is significant latitude-to-latitude variation in the magnitude and sign of these quantities, so that the global average (Table 1) is a small residual of the large and offsetting feedbacks at different latitudes.

Lower clouds experience less cancellation between their SW and LW components. Thus, at any particular latitude, clouds at all levels play important roles in the net cloud feedback. Integrating globally, Table 1 shows that the net cloud feedback is primarily determined by low clouds, with mid-level clouds making a smaller contribution, and high clouds making an even smaller contribution. Alternatively, one could view the net cloud feedback as being set by a negative cloud feedback from low clouds in the SW and mid-level and high clouds in the LW, which is almost entirely cancelled by a positive cloud feedback from mid-level and high clouds in the SW.

We also discussed the scatter in the relation between ΔR_{cloud} and ΔT_s (Fig. 9a), which leads to large uncertainty in the inferred cloud feedback. The scatter arises mainly because ΔR_{cloud} is a small residual of larger, oppositely signed terms that in many cases are themselves statistically significant. Small differences in either of the large terms — whether due to errors in the measurement or calculation or to the fact that clouds are weakly affected by factors

other than ΔT_s — will lead to relatively large changes in ΔR_{cloud} . This produces the scatter in the ΔR_{cloud} vs. ΔT_s relation and to the intrinsic uncertainty in estimates of the cloud feedback. That this work is an analysis of the cloud response to short-term climate variations is an important caveat. Previous work has shown little correlation between the cloud feedback in response to these short-term (mainly ENSO) climate variations and the response to long-term global warming (Dessler, 2010; Colman and Power, 2010; Dessler, 2012). Thus, the implications of this for long-term global warming are unclear. Acknowledgments: This work was supported by NSF grant AGS-1012665 to Texas A&M University. CZ acknowledges support from NASA Earth and Space Science Fellowship grant NNX12AN57H to Texas A&M University. The contribution of MDZ was performed under the auspices of U.S. Department of Energy by Lawrence Livermore National Laboratory (LLNL) under Contract DE-AC52-07NA27344 and was supported by the Regional and Global Climate Modeling Program of the Office of Science at the U. S. Department of Energy.

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Table 1. Summary of global average cloud feedbacks

All values have units of W/m²/K; uncertainties are $\pm 2\sigma$

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MODIS	SW	LW	Net (LW+SW)
cloud feedback			
ΔT_s data set*:			
GISTEMP	+0.47±1.02	-0.48±0.68	-0.02±0.76
HadCRUT4	+0.50±1.20	-0.53±0.80	-0.03±0.90
ERA-interim skin	+0.35±1.01	-0.45±0.68	-0.10±0.76
temperature			
NCDC	$+0.35\pm1.25$	-0.58±0.84	-0.23±0.94
MERRA skin	-0.17±1.02	-0.28±0.69	-0.45±0.76
temperature			
Average	+0.30±1.10	-0.46±0.74	-0.16±0.83
Average (excluding	$+0.42\pm1.13$	-0.51±0.75	-0.10±0.84
MERRA)			
CERES			
cloud feedback			
Average of values in	$+0.14\pm0.78$	$+0.43\pm0.47$	+0.57±0.71
Table 1 of Dessler			
and Loeb (2012)			
(Terra period)			
Breakdown by cloud			
altitude**	0.46+0.60	0.04+0.00	0.50+0.61
$Low (P_{top} > 680 \text{ hPa})$	-0.46±0.68	-0.04±0.09	-0.50±0.61
Mid-level	+0.50±0.36	-0.14±0.11	+0.35±0.28
$(440 < P_{top} < 680 \text{ hPa})$	+0.42+0.79	0.20+0.71	10.1210.25
$High (P_{top} < 440 \text{ hPa})$	+0.43±0.78	-0.30±0.71	+0.13±0.25
Breakdown by cloud			
optical depth**			
Thin $(\tau < 3.6)$	-0.22±0.14	+0.01±0.14	-0.21±0.13
Middle $(3.6 < \tau < 23)$	-0.31±0.76	-0.12±0.44	-0.43 ± 0.56
Thick $(\tau > 23)$	$+0.99\pm0.90$	-0.37±0.38	+0.62±0.54
1 mck (t ~ 23)	' 0.77±0.90	-0.57-0.50	10.02-0.34

^{*}Source of ΔT_s data: GISTEMP: Hansen et al. (2010); HadCRUT4: Morice et al. (2012);

ERA-interim: Dee et al. (2011); the National Climatic Data Center (NCDC): Smith et al.

^{467 (2008);} NASA's Modern Era Retrospective-analysis for Research and Application (MERRA):

⁴⁶⁸ Rienecker et al. (2011);

^{469 **}calculated using GISTEMP ΔT_s . 470

471 Figure captions 472 473 Figure 1. (a) Average cloud fraction in each P_{top} - τ bin (%). (b) Slope of the regression of 474 cloud-fraction anomaly in each bin vs. ΔT_s (%/K). (c-e) The contribution to the net cloud 475 feedback, SW cloud feedback, and LW cloud feedback, respectively, in W/m²/K. Note that the 476 multiplication of cloud radiative kernels with cloud fraction anomalies occurs at every 477 location and is then spatially averaged for display in this figure. Bins where the regression 478 slope is statistically significant (>95%) are marked with black crosses. 479 480 Figure 2. Change in cloud fraction per degree increase in global average ΔT_s (%/K) in (a) the 481 800-1000 hPa layer and (b) the 680-800 hPa layer. The y-axis in these plots is area-weighted 482 latitude. 483 484 Figure 3. The zonal mean cloud feedbacks. The red line is the cloud feedback calculated from 485 MODIS, and the red shading represents the 95% confidence range. The blue line is the 486 feedback from CERES (Dessler, 2010; 2012), and the blue shading represents the 95% 487 confidence range (where they overlap, the shading is purple). 488 489 Figure 4. Spatial distribution of the short-term cloud feedback (W/m2/K) calculated from 490 MODIS observations (left panels) and CERES (middle panels) and the difference (MODIS 491 minus CERES) (right panels). (a-c) are the SW component of cloud feedback, (d-f) are for 492 LW cloud feedback, and (g-i) are for net cloud feedback. The CERES □Rcloud values are 493 from Dessler [2010, 2012]. The y-axis in these plots is area-weighted latitude.

Figure 5. (a) Altitude profile of the change of global mean cloud fraction per degree of global mean surface temperature anomaly (%/K). (b-d) The heavy line shows the contribution to the net, SW, and LW cloud feedbacks, respectively. The error bars indicate the 95% confidence interval. Also shown are the contributions to the cloud feedback at each altitude from changes in τ and cloud fraction, holding all else fixed. Figure 6. (a) Change in cloud fraction per degree increase in global average ΔT_s (%/K) for the 180-50 hPa layer. (b-d) The contribution of cloud changes in this layer to the net, SW, and LW cloud feedbacks in W/m²/K. The v-axis is area-weighted latitude. Figure 7. (a) Slope of the regression of cloud fraction vs. ΔT_s (%/K), as a function of cloud optical depth. (b-d) The heavy line shows the contribution to the net, SW, and LW cloud feedbacks, respectively. The error bars indicate the 95% confidence interval. Also shown are the contributions to the cloud feedback at each optical depth from changes in cloud top height and cloud fraction, holding all else fixed. Figure 8. The zonal mean (a) high, (b) mid-level, and (c) low cloud feedbacks. The black solid line is the total cloud feedback calculated from MODIS. The lines marked with circles and plus signs represent the SW and LW components of the feedback, respectively.

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Figure 9. Scatter plot of global average ΔR_{cloud} vs. ΔT_s for (a) the entire troposphere (50-1000 hPa), (b) the 800-1000 hPa layer, and (c) the 50-800 hPa layer. The least-squares fit and the 2 σ uncertainty of the fit are also plotted.

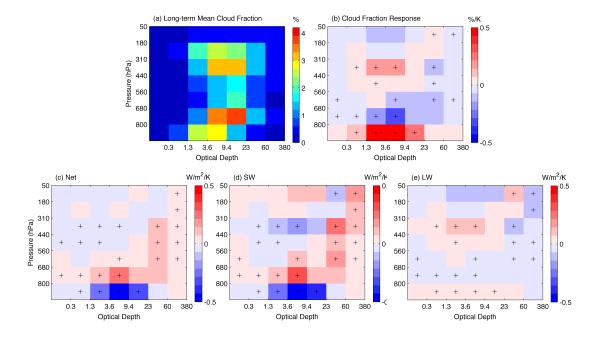


Figure 1. (a) Average cloud fraction in each P_{top} - τ bin (%). (b) Slope of the regression of cloud-fraction anomaly in each bin vs. ΔT_s (%/K). (c-e) The contribution to the net cloud feedback, SW cloud feedback, and LW cloud feedback, respectively, in W/m²/K. Note that the multiplication of cloud radiative kernels with cloud fraction anomalies occurs at every location and is then spatially averaged for display in this figure. Bins where the regression slope is statistically significant (>95%) are marked with black crosses.

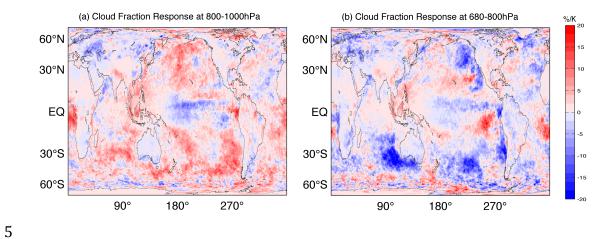


Figure 2. Change in cloud fraction per degree increase in global average ΔT_s (%/K) in (a) the 800-1000 hPa layer and (b) the 680-800 hPa layer. The y-axis in these plots is area-weighted latitude.

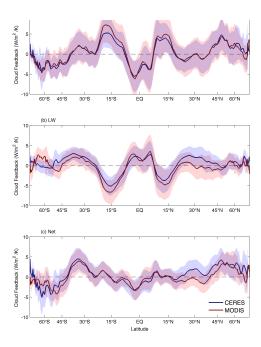


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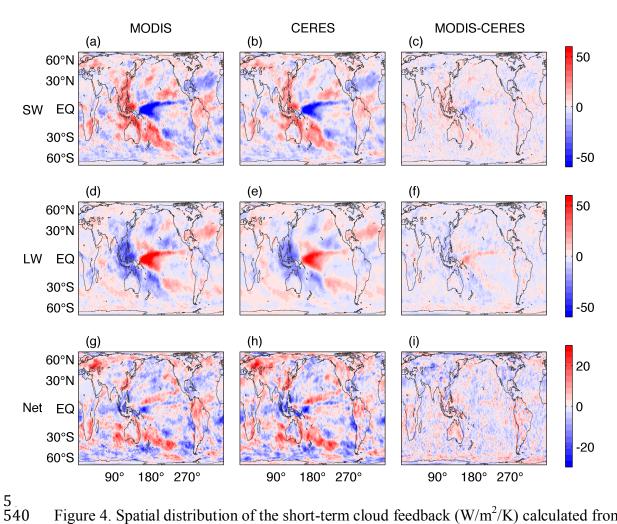


Figure 4. Spatial distribution of the short-term cloud feedback (W/m 2 /K) calculated from MODIS observations (left panels) and CERES (middle panels) and the difference (MODIS minus CERES) (right panels). (a-c) are the SW component of cloud feedback, (d-f) are for LW cloud feedback, and (g-i) are for net cloud feedback. The CERES ΔR_{cloud} values are from Dessler [2010, 2012]. The y-axis in these plots is area-weighted latitude.

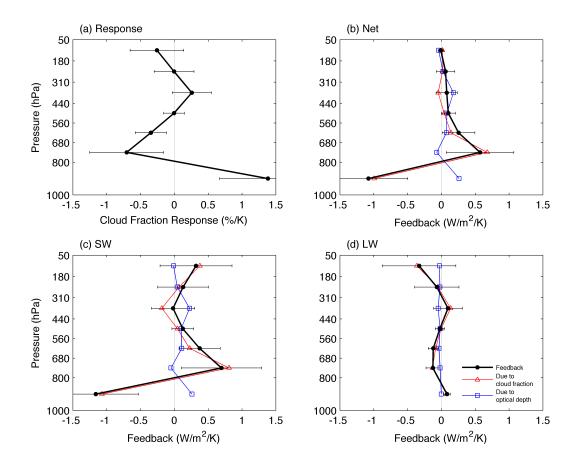


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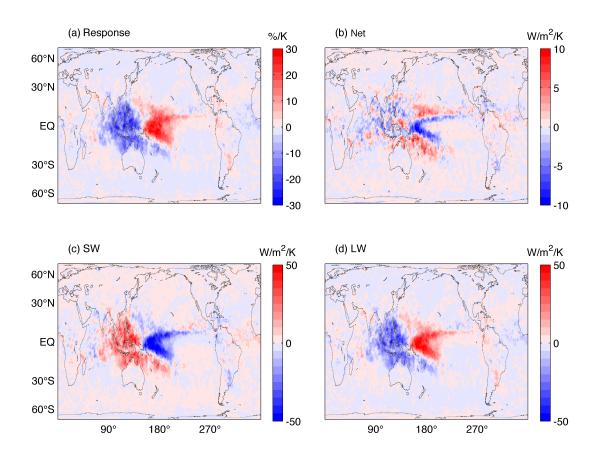


Figure 6. (a) Change in cloud fraction per degree increase in global average ΔT_s (%/K) for the 180-50 hPa layer. (b-d) The contribution of cloud changes in this layer to the net, SW, and LW cloud feedbacks in W/m²/K. The y-axis is area-weighted latitude.

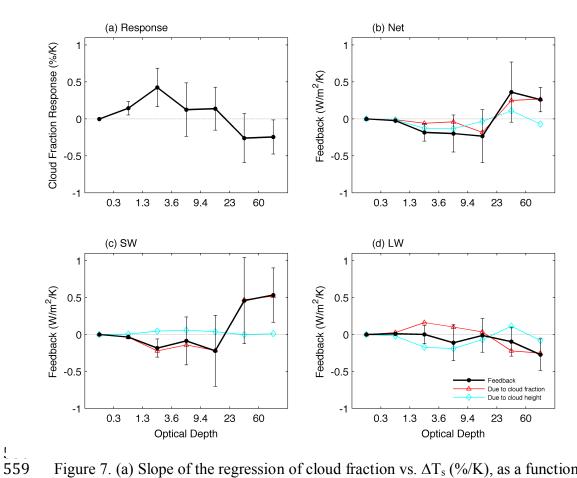


Figure 7. (a) Slope of the regression of cloud fraction vs. ΔT_s (%/K), as a function of cloud optical depth. (b-d) The heavy line shows the contribution to the net, SW, and LW cloud feedbacks, respectively. The error bars indicate the 95% confidence interval. Also shown are the contributions to the cloud feedback at each optical depth from changes in cloud top height and cloud fraction, holding all else fixed.

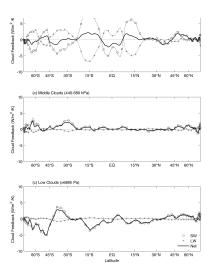


Figure 8. The zonal mean (a) high, (b) mid-level, and (c) low cloud feedbacks. The black solid line is the total cloud feedback calculated from MODIS. The lines marked with circles and plus signs represent the SW and LW components of the feedback, respectively.

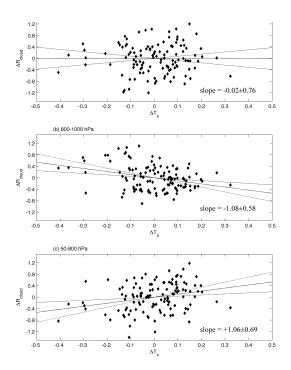


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